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ORIGINAL PAPER

Prediction of lute acoustic quality based on soundboard vibration performance using multiple choice model

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Abstract The vibrational performance of wood materials critical affects the acoustic quality of a lute. The purpose of this research was to apply a multiple choice model to predict the quality of musical instruments based on data on lute soundboard vibrational properties of *Paulownia* wood. In the lute production, lute material selection mainly depends on the subjective evaluation of technicians, which is not only inefficient, but inaccurate. In this study, nine lutes were fabricated. Using the multiple selection model, the lute tone quality was predicted by the soundboard wood vibration data. Compared with the actual value, the dependent value predicted by the count of observations with the maximum probability had 22 erroneous judgments. The model precision is 87.78%. The results confirmed that the prediction model can be used as a guideline for the selection of the soundboard wood in musical instrument plants.

Keywords Multiple choice model · Musical instrument quality · Normal distribution · Vibration performance

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Introduction

Due to its good vibrational characteristics, wood has been used as an important resonance material for musical instruments over the millennia (Damodaran et al. 2015). The unique spectrum of physical properties of wood have made wood the best material for musical instruments up to now (Fletcher and Rossing 1998; Wegst 2006). As a result of the excessive consumption of wood, however, the cost of instruments has increased rapidly. In the search for alternative materials to make traditional musical instruments, some wood-based composites have recently been developed for the top plate of violins (Damodaran et al. 2015). However, the performance of new materials is relatively hard to predict; thus, a model for predicting acoustic quality of an instrument based on the soundboard vibrational performance of raw materials has been needed.

The vibrational characteristics of wood affects the acoustics of a musical instrument. To demonstrate that wood is ideally suitable for the manufacture of idiophones (xylophone bars and chimes), aerophones (flutes and organs), and chordophones (violins and zithers), Wegst (2008) plotted material property charts showing acoustic properties such as sound velocity, characteristic impedance, sound radiation coefficient, and loss coefficient against one another. A new scheme for classifying woods used in stringed instruments was developed by Yoshikawa (2007), which used two regression lines to clearly discriminate the soundboard wood from frame-board wood that are traditionally used for string instruments.

By investigating the vibrational characteristic of wood as a soundboard, Norimoto et al. (1986), Matsunaga et al. (1996) and Kubojima et al. (1997a, b, 1998) found that the wood acoustic vibrational characteristics were significantly affected by performance variables, such as the dynamic elastic modulus E/ρ, elastic modulus E and shear modulus ratio E/G, acoustic radiation damping coefficient R and acoustic impedance ω, etc. Violins were ranked into different grades from the view of acoustic adaptability, aesthetic suitability and comprehensive evaluation using a subjective appraisal method by Buksnowitz (2007). In addition, the index of material properties including sound velocity, sound damping, resonance frequency, dynamic elastic modulus, rigidity, density, ring width, variable coefficient of tree-ring width, ratio of summer wood, fiber length, and dimensional stability were measured, and the material performance was analyzed using a multivariate linear regression method. The main acoustic properties of vene (*Pterocarpus erinaceus*) wood were determined using a method to test free–free flexural vibration (BING device) by Traore et al. (2010).

Multiple choice models as a predictive model have been established to predict fuel consumption and environmental pollution by analyzing how adding alternative fuel passenger cars to the market affects patterns in demand for passenger cars (Ahn et al. 2008) and find market segments for bundles with heterogeneous products in multiple product categories, to estimate individual reservation prices for bundles, and to determine the optimal bundle prices for different market segments (Chung and Rao 2003). Jaggi et al. (2012) proposed modeling household fleet choice as a function of fuel price by using a multiple discrete continuous choice model. Donnell and Connor (1996) utilized a multiple choice model to predict the injury severity from motor vehicle accidents. Gensch (1987) developed a method for quantifiably classifying of population samples based on multiple disaggregate choices.

The multiple choice model has also been widely used in many other fields, such as a family of generalized diagnostic classification models (Dibello et al. 2015) and partial credit item response theory (IRT) (Bo et al. 2013). On account of statistical learning theory, the classification pattern of multiple selection model has received wide attention. Although the dependent variables in econometrics are usually continuous, most of the problems, which in actual applied analyses are selection problems, are expressed by discrete data to build an econometric model, called a discrete selection model. When the dependent variable is discrete and has multiple options ($k \geq 3$) in order selection, it is regarded as a multiple selection model (Ahn et al. 2008).

In this study, the dependent variables in a multiple selection model used to build a lute soundboard evaluation model were nonconsecutive. As a result, the lute soundboard wood property can be precisely predicted. This study also discussed methods of selecting lute materials and provides a scientific approach for forecasting lute soundboard properties.

Materials and methods

Materials and data collection

Lutes made from *Paulownia* wood were used in this study and provided by the Tianjin 1st National Musical Instrument Factory. The wood was air-dried to a moisture content of under 16%. The specifications and dimension of the soundboard wood are shown in Table 1. The dual channel fast Fourier transform analyzer, CF-5220Z, made by Onosokki in Japan was used in the experiment. The sound meter (TES-1350A) and acceleration sensor were used in the test as well. The indexes of dual channel fast Fourier transform analyzer CF-5220Z are listed in Table 2. According to the requirements of the instrument factory, the initial wood material was cut into 36 pieces for making 9 lute soundboards.

A flexural vibration test was used to determine the wood acoustic vibrational properties in this study. The sensitivity was determined and then amplified, filtered and analyzed using a Fast Fourier Transformation (FFT: Japan Ono test equipment origin CF-5220Z models) analyzer to obtain resonance frequencies. Using the obtained resonance frequencies, the dynamic elastic modulus E/ρ, acoustic radiation damping coefficient R, elastic modulus and shear modulus ratio E/G, and acoustic impedance ω, were calculated.

The elastic modulus E (GPa) was calculated as

$$E = \frac{48\pi^2 L^4 \rho f^2}{\beta_n^4 h^2}, \tag{1}$$

where L is the musical instrument sound board length (m), ρ is the sound board density (kg cm^{-3}), f is the sound board resonance frequency (Hz), β_n is the relative constant of wood boundary conditions, and h is the sound board thickness (cm).

The acoustic impedance ω is expressed mathematically as

$$\omega = \rho \upsilon = \sqrt{\rho E}, \tag{2}$$

where ρ is the density of the sample wood (kg cm^{-3}), υ is the surface wave velocity (longitudinal direction) (m/s), E is the dynamic elastic modulus of the wood (GPa $\omega = \rho \upsilon = \sqrt{\rho E}$).

The acoustic radiation damping coefficient is calculated as

$$R = \frac{v}{\rho} = \sqrt{\frac{E}{\rho^3}}. \tag{3}$$

During the experiments, 36 soundboards were tested with five determinations for each board. Based on the above methods, 180 groups of data were collected.

Table 1 Parameters of soundboard wood

Name	Species	No. of pieces	Length (cm)	Width (cm)	Thickness (cm)	Density (g cm^{-3})	No. of annual rings
Lute	*Paulownia*	36	36.42–39.48	16.42–19.49	0.96 ± 0.02	0.23–0.29	7.50–12.50

Table 2 CF-5220Z Dual channel FFT analyzer technical indexes

Index	Settings
Operation frequency	10 mHz–100 kHz
Microphone frequency	20 Hz–20 kHz
Sampling frequency	2.56 times of measurement range
Sampling node	64–4096 (commonly used as 2048)
Frequency distinguish ability	25, 50, 100, 200, 400, 800, 1600 lpi
Microphone sensibility	−29 ± 3 dB (0 dB = 1 v/pa)

Experienced experts in music and lute performance were invited to evaluate the acoustic quality (sound loudness, dynamic range, sound length and tone, etc.) of the instrument products objectively according to three grades (there is no grade criterion for Lute in China. We made 9 lutes and invited 3 experts to evaluate their quality. According to the quality evaluation from the experts, we sorted the 9 lutes into 3 grades. The best three were Grade 1 and the worst three were Grade 3).

Normality tests

The normality of the values for the dynamic elastic modulus E/ρ, acoustic radiation damping coefficient R, elastic modulus and shear modulus ratio E/G and acoustic impedance ω were tested using Kolmogorove–Smirnov (KS) method in SPSS.

Multiple choice model principle

Multiple choice analysis is a method to optimize the sequence of program combination in the model. It is used to examine the change rule of relevant unknown variables, which is constructed by measured, well-aligned data (Jaggi et al. 2012). The principle of the multiple choice model is described as follows:

If the multiple ordered choice model is

$$P(y = y_i|\mathbf{X}_i, \boldsymbol{\beta}) = P(y = y_i|x_0, x_1, x_2, \ldots, x_p) \quad (4)$$

where y_i has m ranked choices, in which i is 0, 1, 2, $m-1$, respectively. y_i is a discrete variable. To build a multiple choice model, an unobservant hidden variable, y_i^*, is introduced.

$$y_i^* = \mathbf{X}_i'\boldsymbol{\beta} + \varepsilon_i^* \quad (5)$$

where ε_i^* is a stochastic disturbance that is independent identically. The parameter estimation of the model is based on the maximum likelihood method.

In addition, the discrete choice y_i and the hidden variable y_i^* have a one-to-one relationship.

$$y_i = \begin{cases} 0, & y_i^* \le c_1 \\ 1, & c_1 < y_i^* \le c_2 \\ 2, & c_2 < y_i^* \le c_3 \\ & \vdots \\ m-1 & c_{m-1} < y_i^* \end{cases} \quad (6)$$

$F(x)$ is the distribution function of ε_i^*, the probability of dependent variable y_i can be calculated,

$$\begin{aligned} &P(y_i = 0) = F(c_1 - \mathbf{X}'\boldsymbol{\beta}) \\ &P(y_i = 1) = F(c_2 - \mathbf{X}'\boldsymbol{\beta}) - F(c_1 - \mathbf{X}'\boldsymbol{\beta}) \\ &P(y_i = 2) = F(c_3 - \mathbf{X}'\boldsymbol{\beta}) - F(c_2 - \mathbf{X}'\boldsymbol{\beta}) \\ &\vdots \\ &P(y_i = m-1) = 1 - F(c_{m-1} - \mathbf{X}'\boldsymbol{\beta}) \end{aligned} \quad (7)$$

where y_i has m is ranked choices, c is critical value, $c_i(i = 1, 2, \ldots, m-1)$ is a parameter to be estimated using the model coefficients.

In addition, the distribution function $F(x)$ generally can have three common forms, which are normal distribution, logistic distribution and extreme value distribution. Since the distribution function was chosen by the actual model data, the distribution tests were carried out before using the multiple choice model.

Results and discussion

Normality tests

Using SASS, the results of the normality tests indicated that all the main parameters of the wood acoustic vibration property,E/ρ, R, E/G and ω, agreed with the hypotheses, i.e., they did NOT differ from a normal distribution. As an example, the normality test results of E/ρ are shown in Fig. 1a, b using the KS method in SPSS. When the KS tests were used for the normality test for the dynamic elastic modulus E/ρ, a hypothesis of no significant difference from the normal distribution was applied. After running SPSS, the significance was obtained as 0.200, which indicated that the hypothesis was accepted because the

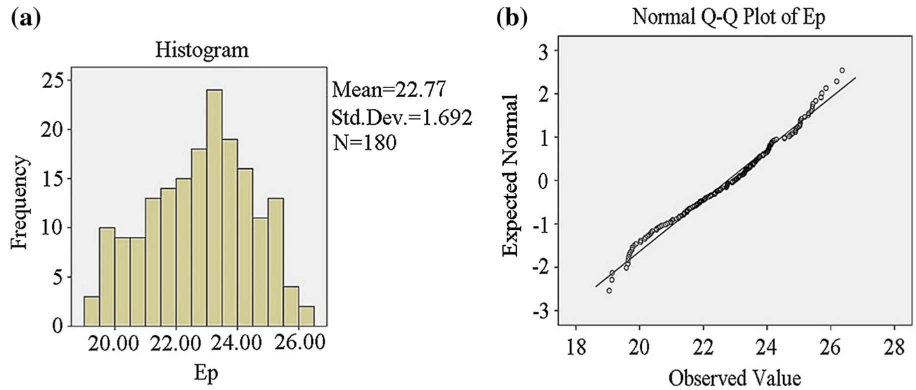

Fig. 1 The normality test results for dynamic elastic modulus E/ρ. **a** Distribution and **b** expected normal

obtained value of 0.200 was greater than $\alpha = 0.05$, the preset value to test the normality. Thus, the E/ρ data were normally distributed as shown in Fig. 1a.

Model development

E/ρ, E/G, R, and W are abbreviation of dynamic elastic modulus, elastic modulus and shear modulus ratio, acoustic radiation damping coefficient, and acoustic impedance of soundboard wood. The instrument acoustical quality is ranked into three grade (1, 2, 3). 180 groups experimental data was calculated. 60 groups of each grade were used to train model, 60 groups of each grade from the rest 120 groups were used to verify model (120 groups of each grade were selected from the total 180 groups, 60 groups were used to train model, 60 groups were used to verify the classification. EViews 5.0 is applied to build the multiple choice model of resonant board vibration property and acoustic grade of different instrument. The result is as follows:

Based on the theoretical foundation above, EViews5.0 is employed to build multiple choice model of lute soundboard wood vibrational properties and instrument acoustic grade. The results calculated using a normal distribution are shown in Table 3.

Table 3 shows P of the test statistic z of the independent variable R is $0.7310 > 0.1$. R is at 0.1 confidence level, and the influence of R on ranking is nonsignificant, so R has to be eliminated. Table 4 is the adjusted model.

Table 4 shows the independent variables in the multiple choice model of the lute soundboard wood vibrational property and instrument acoustic grade are significant at 0.01 confidence level.

$$y^* = -0.5303E/\rho + 0.0378E/G + 4.9907\omega$$
$$(-5.8033) \quad (6.3498) \quad (5.5240)$$

Forecasting grade assessment analysis

LR statistic = 64.1842, fake R^2 (likelihood index) = 0.1623.

The result of statistical test shows that an predictive effect of the model is reasonable and can be used for analysis.

From the view of the model parameters, if other variables are invariable, when E/ρ of the lute soundboard wood vibrational property increases 1 unit, y^* will decrease 0.5303 unit; when E/G increases 1 unit, y^* will increase 0.0378 unit; when ω increases 1 unit, y^* will increase 4.9907 unit. The result shows that the impact of R on grade evaluation is negligible. E/G, E/ρ has an inconspicuous impact as well, but the impact of E/ρ is positive, while the impact of E/G is negative. ω has a significant negative impact on grade evaluation. y_i has three grades, so the model has 2 critical points, its estimated values are $\hat{c}_1 = 3.4210$, $\hat{c}_2 = 4.4897$. Incremental critical value shows the model has an ideal predictive effect.

The original data is used in the model to calculate $\hat{y}^*$. Then $\hat{y}^*$ is compared with the critical value between $\hat{c}_1 = 3.4210$ and $\hat{c}_2 = 4.4897$, and the predicted precision of the model is determined. The predicted value of the model is shown in Fig. 2, where, 1–60 is defined as grade 1, 61–120 is grade 2, 121–180 is grade 3. Accuracy of the model based on the predicted result is shown in Table 5.

Table 5 shows the model has a low accuracy, the predicted precision is 55%. Actually, the predicted grade based on the predicted value, and the critical value may not the final result. When the predicted value is near critical value, the predicted value is not within the critical value range, but the result can be still correct.

When the predicted value expectation possibility is considered, the expectation of every option can be predicted. EViews5.0 is applied to the calculated multiple choice model E-P figure of the predicted instrument acoustical grade; the result is shown in Fig. 2.

Table 3 Multiple choice model of the lute soundboard wood vibrational characteristics and sound quality levels

	Coefficient	Standard error	z-statistic	Probability
E/ρ	−0.546009	0.102908	−5.305811	0.0000
E/G	0.037202	0.006180	6.019618	0.0000
R	0.035157	0.102276	0.343746	0.7310
W	5.217800	1.140762	4.573961	0.0000
Limit points				
LIMIT_2:C(5)	3.857582	1.796702	2.147035	0.0318
LIMIT_3:C(6)	4.925907	1.804498	2.729793	0.0063
Akaike information criterion	1.906651	Schwarz criterion		2.013083
Logarithm likelihood	−165.5986	Hannan–Quinn criterion		1.949805
Restraints logarithm likelihood	−197.7502	Average logarithm likelihood		−0.919992
LR statistic (4 *df*)	64.30320	LR index (Pseudo-R^2)		0.162587
Probability (LR statistic)	3.61E−13			

LR likelihood ratio, *df* degree of freedom

Table 4 Adjusted multiple choice model of lute soundboard wood vibrational property and acoustical quality grade

	Coefficient	Standard error	z-statistic	Probability
E/ρ	−0.530280	0.091375	−5.803338	0.0000
E/G	0.037785	0.005951	6.349805	0.0000
W	5.217800	1.140762	5.523973	0.0000
Limit points				
LIMIT_2:C(4)	3.421039	1.257908	2.719625	0.0065
LIMIT_3:C(5)	4.489687	1.269840	3.535632	0.0004
Akaike information criterion	1.896201	Schwarz criterion		1.984894
Logarithm likelihood	−165.6581	Hannan–Quinn criterion		1.932162
Restraints logarithm likelihood	−197.7502	Average logarithm likelihood		−0.920323
LR statistic (4 *df*)	64.18423	LR index (Pseudo-R^2)		0.162286
Probability (LR statistic)	7.49E−14			

LR likelihood ratio, *df* degree of freedom

Figure 2 shows that the predicted correct points for Grade 1 are located in the interval of the abscissa ranging from 1 to 60 and at the interval of ordinate ranging from -1 to c_1. The predicted critical points for Grade 1 are in the abscissa 1–60 and c_1 to c_2. From here, the system returns to error points. Within abscissa 1–6 and to 5 interval ranges, those points are denoted as Grade 1 forecast of error points. Within abscissa 61–120 and ordinate c, and c range, the points are denoted Grade 2 forecast of right side points. In the abscissa 61–120, and below and above the ordinate c, the points are Grade 2 forecast of error points. The y 121–180 and vertical coordinates to within 6 points correctly predict level 3. For y 121–180 and c, with c for level 3 forecast within the critical point, this system is classified as an error. The points within the range of y 121–180 and $y - 1$ are denoted level 1 errors.

Table 6 shows that every grade has 60 group samples, and the three grades have 180 total groups. Compared with the actual value, the dependent variable predicted by the multiple choice model at the count of observations (obs.) with the maximum (max.) probability (prob.) has $6 + 5 + 11 = 22$ errors. The model precision is $(180 - 22)/180 \times 100 = 87.78\%$.

Conclusions

This study tested the vibrational performance of the lute soundboard and extracted the main indexes of wood acoustic properties. Using the multiple choice model, based on the soundboard selection, we developed a forecasting model for lute soundboard acoustic quality. It implemented a partial prediction of lute acoustic quality, and lute product quality was evaluated before the manufacturing process. For the multiple selection model of lute tone quality predicted by wood soundboard, compared with the actual

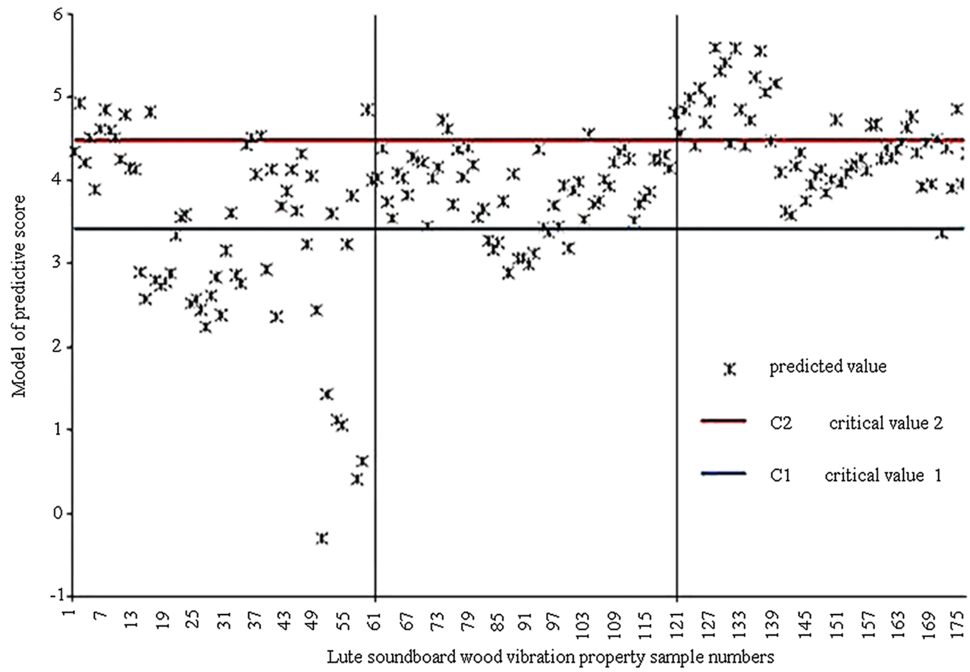

Fig. 2 Multiple choice model diagram of predicted instrument acoustic grade

Table 5 Multiple choice model evaluation statistics of predicted instrument acoustical grade

Actual grade	Predicted grade			No. of errors	Predictive accuracy (%)
	1	2	3		
1	28	21	11	32	46.67
2	10	46	4	14	76.67
3	1	34	25	35	41.67
Total	39	101	40	81	55.00

Table 6 Multiple choice model E–P diagram of predicted grade of instrument acoustics

Value	Count	Count of obs. with max prob.	Error	Sum of all probabilities	Error
1	60	54	6	60.120	−0.120
2	60	55	5	58.821	1.179
3	60	71	−11	61.059	−1.059

value, the dependent value predicted by the maximum probability had 22 erroneous judgments. The model precision is 87.78%. The developed model can be used as a practical guideline for estimating instrument quality.

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